

# bayestestR: Understanding and Describing Effects and their Uncertainty, Existence and Significance in the Bayesian Framework

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## Introduction

The Bayesian framework for statistics is quickly gaining in popularity among scientists, for reasons such as reliability and accuracy (particularly in noisy data and small samples), the possibility of incorporating prior knowledge into the analysis and the intuitive interpretation of results (Andrews and Baguley 2013; Etz and Vandekerckhove 2016; Kruschke 2010; Kruschke, Aguinis, and Joo 2012; Wagenmakers et al. 2018). Adopting the Bayesian framework is more of a shift in the paradigm than a change in the methodology; All the common statistical procedures (*t*-tests, correlations, ANOVAs, regressions, etc.) can also be achieved within the Bayesian framework. One of the core difference is that in the *frequentist* view, the effects are fixed (but unknown) and data are random. On the other hand, instead of having single estimates of the “true effect”, the Bayesian inference process computes the probability of different effects *given the observed data*, resulting in a distribution of possible values for the parameters, called the *posterior distribution*.

Effects in the Bayesian framework can be described by characterizing their posterior distribution. Commonly reported indices include measures of centrality (e.g., the median, mean or MAP) and uncertainty (the *credible* interval). Cum grano salis, these are considered the counterparts to the coefficient point-estimates and confidence intervals of the frequentist framework. Additionally, **bayestestR** also focuses on implementing a Bayesian null-hypothesis testing framework (in a Bayesian meaning, i.e., extended to general testing of “effect existence”) by providing access to both established and exploratory indices of effect *existence* and *significance* (such as the ROPE, John K Kruschke and Liddell (2018); the MAP-based p-value, Mills (2018); or the Probability of Direction - *pd*).

Existing R packages allow users to easily fit a large variety of models and extract and visualize the posterior draws. However, most of these packages only return a limited set of indices (e.g., point-estimates and CIs). **bayestestR** provides a comprehensive and consistent set of functions to analyze and describe posterior distributions generated by a variety of models objects, including popular modeling packages such as **rstanarm** (Goodrich et al. 2018), **brms** (Bürkner and others 2017) or **BayesFactor** (Morey and Rouder 2018), thus appearing as a useful tool supporting the usage and development of Bayesian statistics. The main functions are described below, and a full documentation is available on the package’s website.

## Examples of Features

The following demonstration of functions in **bayestestR** is accompanied by figures to illustrate the conceptual ideas behind the related indices. However, **bayestestR** functions also include plotting capabilities via the **see** package (Lüdtke et al. 2019).

### Indices of Centrality: Point-estimates

**bayestestR** offers two functions to compute point-estimates from posterior distributions: `map_estimate()` and `point_estimate()`, the latter providing options to calculate the mean, median or MAP estimate of a posterior distribution. `map_estimate()` is a convenient function to calculate the MAP estimate directly.

The **posterior mean** minimizes expected *squared* error, whereas the **posterior median** minimizes expected *absolute* error (i.e. the difference of estimates from true values over samples). The highest **Maximum A Posteriori** (MAP) estimate is the most probable value of a posterior distribution.

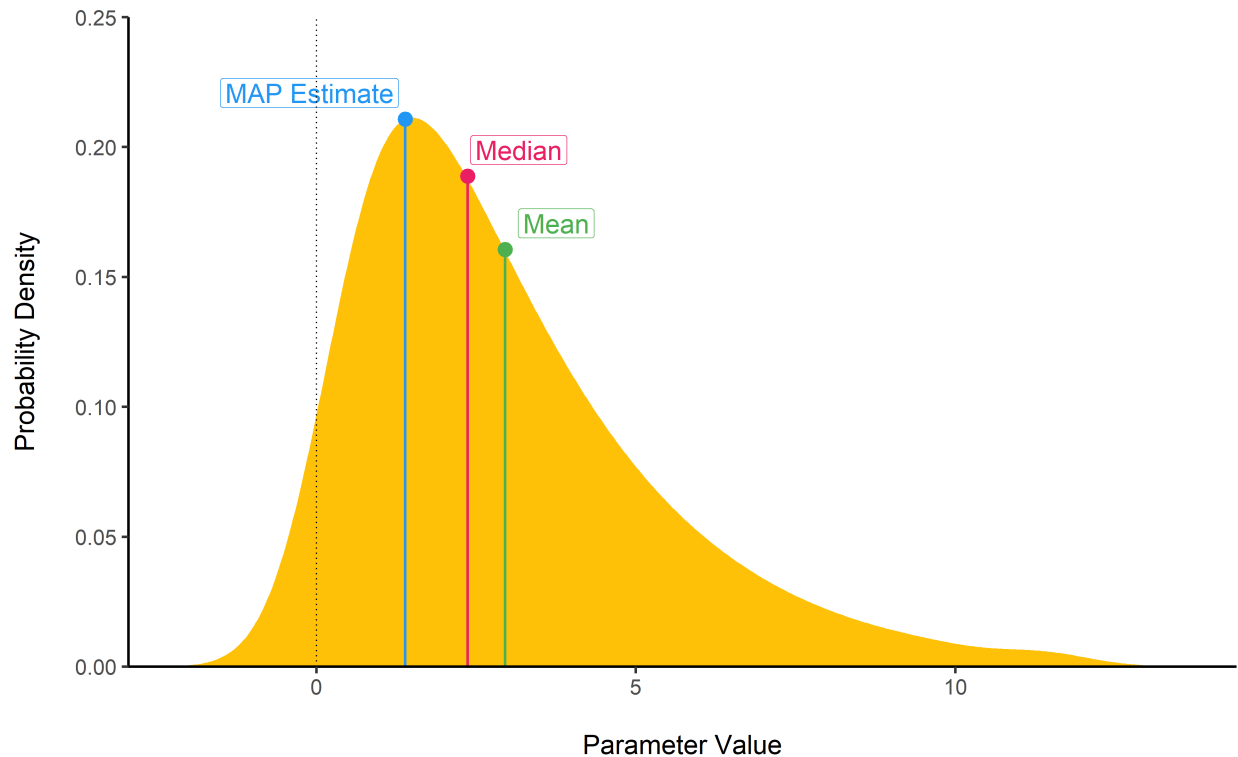


Figure 1: Indices of centrality of the posterior distribution: the mean (in green), median (in red), and MAP (in blue)

```
set.seed(1)
posterior <- rchisq(100, 3)
map_estimate(posterior)
#> MAP = 1.46

point_estimate(posterior)
#> Median = 2.31

point_estimate(posterior, centrality = "mean")
#> Mean = 2.96

point_estimate(posterior, centrality = "map")
#> MAP = 1.46
```

## Indices of Uncertainty: HDI and CI

To measure the uncertainty in the estimation, **bayestestR** provides two functions: `ci()`, the “classical”, equal-tailed credible interval, and `hdi()`, the highest density interval.

`hdi()` computes the **Highest Density Interval (HDI)** of a posterior distribution, i.e., the interval which contains all points within the interval have a higher probability density than points outside the interval. The HDI can be used in the context of Bayesian posterior characterisation as **Credible Interval (CI)**, however, HDIs have a particular property: Unlike equal-tailed intervals (see `ci()`) that typically exclude 2.5% from each tail of the distribution, the HDI is *not* equal-tailed and therefore always includes the mode(s) of posterior distributions.

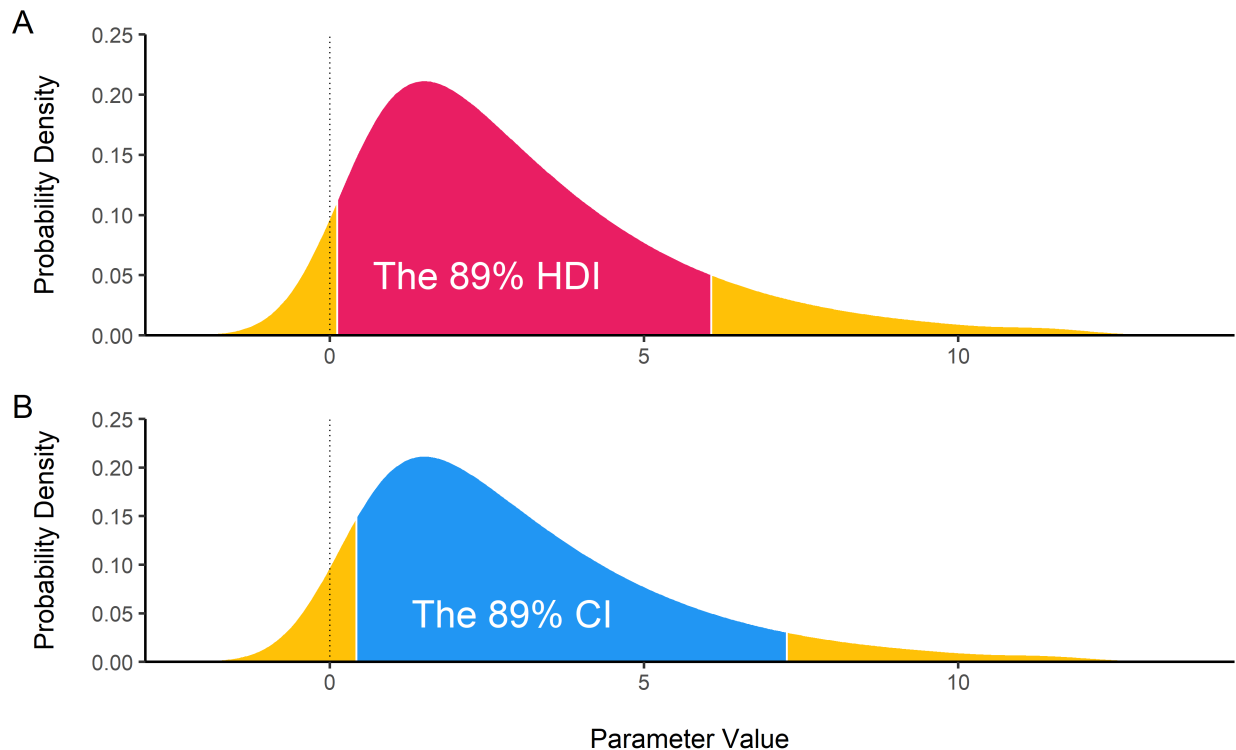


Figure 2: Indices of uncertainty of the posterior distribution: (A) the 89% HDI; (B) the 89% CI.

By default, `hdi()` and `ci()` return the 89% intervals (`ci = 0.89`), deemed to be more stable than, for instance, 95% intervals. An effective sample size of at least 10,000 is recommended if 95% intervals should be computed (Kruschke 2015). Moreover, 89 is the highest prime number that does not exceed the already unstable 95% threshold (McElreath 2018).

```
hdi(posterior)
#> # Highest Density Interval
#>
#>      89% HDI
#> [0.11, 6.05]

ci(posterior)
#> # Credible Interval
#>
#>      89% CI
#> [0.42, 7.27]
```

## Null-Hypothesis Significance Testing (NHST)

### ROPE

`rope()` computes the proportion (in percentage) of the HDI (default to the 89% HDI) of a posterior distribution that lies within a region of practical equivalence (see figure 3, panel A).

Statistically, the probability of a posterior distribution of being different from 0 does not make much sense (the probability of it being different from a single point being infinite). Therefore, the idea underlining ROPE is to let the user define an area around the null value enclosing values that are *equivalent to the null* value for

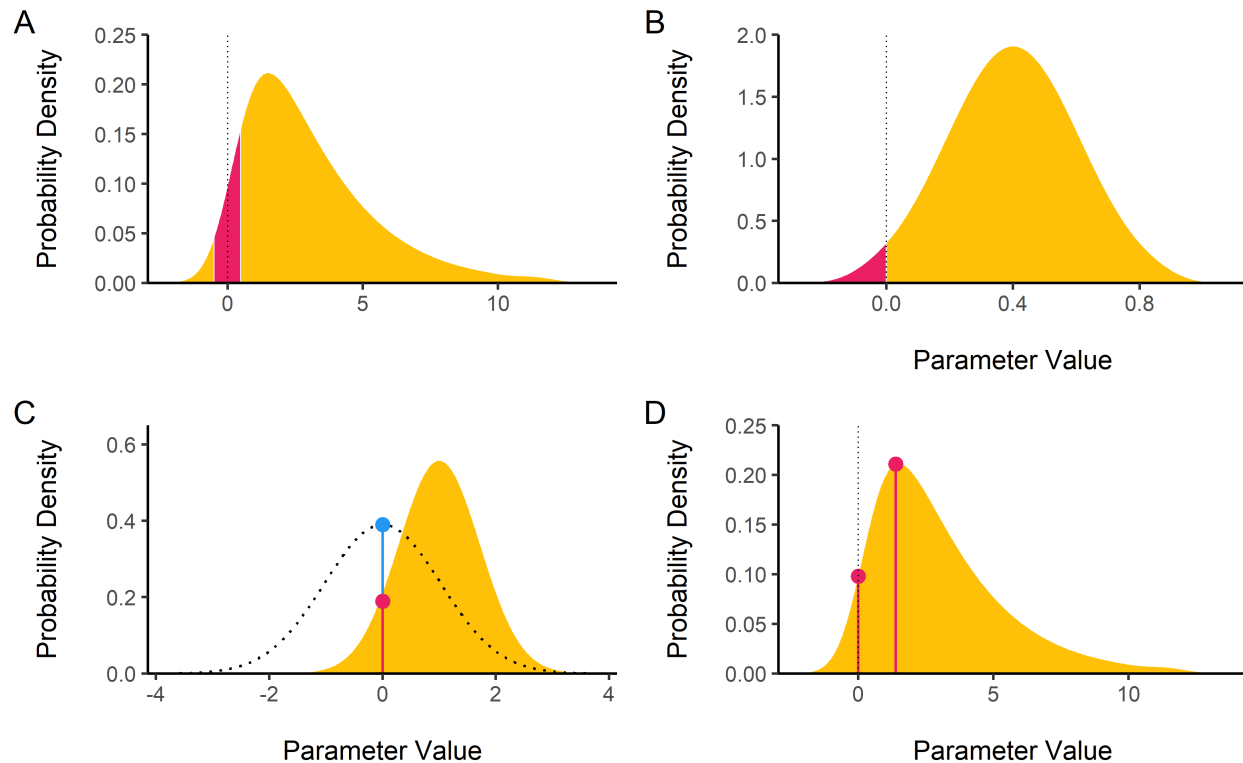


Figure 3: Null-Hypothesis Significance Testing: (A) The ROPE; (B) The Probability of direction; (C) The Savage-Dickey Bayes factor; (D) The p-MAP.

practical purposes (John K Kruschke and Liddell 2018; John K Kruschke 2018).

Kruschke suggests that such null value could be set, by default, to the -0.1 to 0.1 range of a standardized parameter (negligible effect size according to Cohen, 1988). This could be generalized: For instance, for linear models, the ROPE could be set as  $0 \pm .1 * sd(y)$ . This ROPE range can be automatically computed for models using the `rope_range` function.

The proportion of the 95% HDI (or 90%, considered more stable) that falls within the ROPE can be used as an index for “null-hypothesis” testing (as understood under the Bayesian framework, see `equivalence_test`).

```
rope(posterior, range = c(-0.5, 0.5))
#> # Proportion of samples inside the ROPE [-0.50, 0.50]:
#>
#> inside ROPE
#> 8.89 %
```

### Test for Practical Equivalence

`equivalence_test()` is a **Test for Practical Equivalence** based on the “HDI+ROPE decision rule” (John K Kruschke 2018) to check whether parameter values should be accepted or rejected against an explicitly formulated “null hypothesis” (i.e., a ROPE).

The percentage of the HDI that falls within the ROPE serves as decision rule: If the HDI is completely outside the ROPE, the “null hypothesis” for this parameter is “rejected”. If the ROPE completely covers the HDI, i.e., all most credible values of a parameter are inside the region of practical equivalence, the null hypothesis is accepted. Else, it’s undecided whether to accept or reject the null hypothesis.

```
library(rstanarm)
model <- stan_glm(mpg ~ wt + gear, data = mtcars)
equivalence_test(model)
#> # Test for Practical Equivalence
#>
#> ROPE: [-0.60 0.60]
#>
#> Parameter      H0 inside ROPE      89% HDI
#> (Intercept) Rejected      0.00 % [30.82 47.02]
#> wt Rejected      0.00 % [-6.63 -4.39]
#> gear Undecided      52.54 % [-1.76 1.23]
```

As said above, for regression models `equivalence_test()` will automatically find an appropriate range for the ROPE. However, it is also possible to define a custom range using the `range`-argument.

```
equivalence_test(posterior, range = c(-0.5, 0.5))
#> # Test for Practical Equivalence
#>
#> ROPE: [-0.50 0.50]
#>
#> H0 inside ROPE      89% HDI
#> Undecided      8.89 % [0.11 6.05]
```

### Probability of Direction (*pd*)

`p_direction()` computes the **Probability of Direction** (*pd*, also known as the Maximum Probability of Effect - *MPE*). It varies between 50% and 100% (i.e., 0.5 and 1) and can be interpreted as the probability (expressed in percentage) that a parameter (described by its posterior distribution) is strictly positive or negative (whichever is the most probable). It is mathematically defined as the proportion of the posterior distribution that is of the median's sign (see figure 3, panel B).

The demonstration of the *pd* only makes sense for distributions that in principle can have both positive and negative values, so for the next example a normal distribution is used with values approximately ranging from  $-0.1$  to  $0.9$ .

```
p_direction(distribution_normal(100, 0.4, 0.2))
#> # Probability of Direction (pd)
#>
#> pd = 98.00%
```

### Bayes Factor

`bayesfactor_savagedickey()` computes the ratio between the density of a single value (typically the null) in two distributions. When these distributions are the prior and the posterior distributions, this ratio can be used to examine the degree by which the mass of the posterior distribution has shifted further away from or closer to the null value (relative to the prior distribution), thus indicating if the null value has become less or more likely given the observed data (see figure 3, panel C). The Savage-Dickey density ratio is also an approximation of a Bayes factor comparing the marginal likelihoods of the model against a model in which the tested parameter has been restricted to the point null (Wagenmakers et al. 2010).

```
prior <- rnorm(1000, mean = 0, sd = 1)
posterior <- rnorm(1000, mean = 1, sd = 0.7)

bayesfactor_savagedickey(posterior, prior, direction = "two-sided", hypothesis = 0)
```

## MAP-based p-value

`p_map()` computes a Bayesian equivalent of the p-value, related to the odds that a parameter (described by its posterior distribution) has against the null hypothesis ( $h_0$ ) using Mills' *Objective Bayesian Hypothesis Testing* framework (Mills 2018; Mills and Parent 2014). It is mathematically based on the density at the Maximum A Priori (MAP) and corresponds to the density value at 0 divided by the density of the MAP estimate (see figure 3, panel D).

```
p_map(posterior)
#> # MAP-based p-value
#>
#> p (MAP) = 0.000
```

## Licensing and Availability

**bayestestR** is licensed under the GNU General Public License (v3.0), with all source code stored at GitHub (<https://github.com/easystats/bayestestR>), with a corresponding issue tracker for bug-reporting and feature enhancements. In the spirit of honest and open science, we encourage requests/tips for fixes, feature updates, as well as general questions and concerns via direct interaction with contributors and developers.

## Acknowledgments

**bayestestR** is part of the *easystats* ecosystem (relying on the **insight** package to access information contained in models; Lüdtke, Waggoner, and Makowski (2019)), a collaborative project created to facilitate the usage of R. Thus, we would like to thank the council of masters of easystats, all other padawan contributors, as well as the users.

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